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Validation of the Artificial Intelligence Development Model in Banks' Financial Services Based on Structural Equation Modeling

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ABSTRACT

This study was conducted with the aim of validating the artificial intelligence development model in banks' financial services. In terms of purpose, the research is applied, and in terms of methodology, it is descriptive and based on structural equation modeling. The statistical population consisted of the presidents and senior executives of selected public and private banks in Iraq located in the cities of Baghdad, Erbil, Najaf, and Basra. The research instrument was a 24-item questionnaire designed on a five-point Likert scale, which was developed electronically and its link was distributed to bank executives via official email. The collected data were analyzed using structural equation modeling (SEM). The results indicated that both convergent validity and discriminant validity of the constructs were confirmed, and the Cronbach's alpha coefficient exceeded 0.70, demonstrating acceptable internal consistency reliability. All model fit indices were within the acceptable range, indicating an appropriate fit of the measurement model and alignment of the observed data with the hypothesized structure. Accordingly, the final conclusion is that the artificial intelligence development model in banks' financial services—comprising the dimensions of technological infrastructure, data quality, cybersecurity, organizational culture, regulatory compliance, and artificial intelligence adoption—possesses satisfactory validity and can be effectively applied within the banking system of Iraq.

Keywords: Artificial intelligence; Financial services; Bank.

Introduction

The global banking industry is experiencing a structural transformation driven by the rapid advancement and institutionalization of artificial intelligence technologies. Contemporary financial systems are no longer centered solely on traditional information technologies but are increasingly built upon intelligent architectures that enable automated decision-making, predictive analytics, real-time risk evaluation, and highly personalized customer engagement (1-3). This transition has given rise to the conceptual framework of Banking 4.0, wherein artificial intelligence functions as the core infrastructure underlying service delivery, organizational governance, and strategic competitiveness (4, 5). Banks worldwide are therefore compelled to redesign their financial service models in response to digital disruption and escalating customer expectations.

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Artificial intelligence in banking encompasses a broad ecosystem of applications including intelligent credit scoring, automated fraud detection, algorithmic trading, robo-advisory services, customer relationship management, conversational banking through chatbots, and cybersecurity risk management (1, 6, 7). Empirical research consistently demonstrates that AI-enabled banking significantly improves service quality, customer satisfaction, and operational efficiency, particularly within digitally emerging markets (7, 8). However, the effectiveness of these technologies is not determined by technological sophistication alone; rather, it is contingent upon a complex interaction among organizational culture, data governance, regulatory structures, cybersecurity systems, and human capital readiness (9, 10).

Recent literature increasingly conceptualizes artificial intelligence adoption in banking as a systemic transformation rather than a discrete technological upgrade. (2) argues that AI and machine learning are fundamentally redefining financial governance structures, decision architectures, and competitive dynamics. Similarly, (11) conceptualizes artificial intelligence as the driving force behind the reconfiguration of banking value chains toward intelligence-based service ecosystems. While these transformations offer substantial performance benefits, they simultaneously introduce new vulnerabilities related to data integrity, cybersecurity threats, regulatory compliance complexity, and workforce adaptation (10, 12).

The organizational implications of artificial intelligence deployment present one of the most significant challenges for banking institutions. (13) demonstrates that the implementation of AI-based financial reporting systems necessitates fundamental restructuring of internal workflows, role definitions, and performance evaluation mechanisms. Human capital capability has therefore emerged as a critical determinant of AI success. Banking employees must acquire new competencies in data analytics, algorithmic interpretation, digital ethics, and collaborative decision-making (10, 14). Inadequate organizational culture alignment can substantially undermine AI initiatives even in institutions possessing advanced technological infrastructure.

Data quality constitutes another foundational pillar of artificial intelligence development. Without reliable, accurate, and well-governed data, AI models generate unstable predictions and biased outcomes. (15) empirically demonstrates that improvements in financial reporting effectiveness and efficiency are strongly mediated by the quality of data ecosystems supporting artificial intelligence systems. Similarly, (16) emphasizes that predictive analytics in banking is fundamentally constrained by institutional data integration capacity and governance maturity. Consequently, any comprehensive AI development framework must explicitly integrate data quality management as a core construct.

Cybersecurity and regulatory compliance further complicate the deployment of artificial intelligence in financial services. As AI systems become deeply embedded in transaction processing and risk management, banks face heightened exposure to cyber threats, algorithmic manipulation, privacy breaches, and regulatory scrutiny (12, 17). (17) highlights that the integration of artificial intelligence with blockchain technology significantly enhances transparency, auditability, and regulatory trust, particularly within Islamic banking environments. Nevertheless, regulatory systems frequently lag behind technological innovation, creating legal uncertainty that may impede institutional adoption (9, 18).

Customer-facing applications of artificial intelligence further illustrate the strategic importance of organizational readiness. (18) finds that customer adoption of AI-based mobile banking is shaped by perceived intelligence, anthropomorphic design features, trust, and emotional engagement. Likewise, (6) reports that AI-driven service interfaces fundamentally transform bank–customer relationships by shifting interaction paradigms from transactional to relational engagement. These findings reinforce the necessity of aligning technological innovation with organizational culture and consumer psychology.

Despite the expanding research base, major gaps remain. Existing studies frequently investigate isolated dimensions of artificial intelligence implementation without evaluating integrated development frameworks that capture the full institutional complexity of banking ecosystems (1, 3). Moreover, rigorous empirical validation of such frameworks using advanced multivariate techniques such as structural equation modeling remains limited, particularly in Middle Eastern banking systems. While (9) provides evidence that artificial intelligence moderates innovative financial processes, comprehensive validation of multidimensional AI development models remains underexplored.

The Iraqi banking sector represents a particularly important context for this investigation. Iraq's financial system is undergoing modernization while facing distinctive challenges associated with infrastructure development, regulatory evolution, organizational restructuring, and cybersecurity governance. Understanding how artificial intelligence development can be systematically structured and empirically validated within this environment carries substantial implications for both academic theory and financial policy.

Accordingly, this study integrates contemporary theoretical and empirical perspectives to construct and empirically validate a comprehensive artificial intelligence development model for banking financial services, grounded in the dimensions of technological infrastructure, data quality, cybersecurity, organizational culture, regulatory compliance, and artificial intelligence adoption (1, 9, 10, 19).

The aim of this study is to validate a comprehensive artificial intelligence development model for banking financial services using structural equation modeling within the context of Iraqi banks.

Methods and Materials

The present study was applied in terms of purpose and employed a descriptive research design based on structural equation modeling. The statistical population consisted of the presidents and senior executives of selected banks in Iraq. These banks included both public and private institutions that had at least three operational branches in major Iraqi cities such as Baghdad, Erbil, Najaf, Basra, and other metropolitan areas. The selection of this population was based on the strategic role of bank executives in decision-making processes related to technological development and financial service innovation, particularly in the domain of artificial intelligence adoption. Participation in the study was voluntary, and all respondents were informed of the objectives of the research and the academic nature of the data collection process prior to participation. After the completion of the data collection period, a total of 283 questionnaires were returned. Following a screening process in which questionnaires with more than ten percent missing responses were excluded, 285 valid questionnaires remained for statistical analysis. These responses constituted the final sample used in the study and were considered sufficient for conducting structural equation modeling given the number of latent variables and measurement indicators involved in the proposed model.

Data were collected using a researcher-developed questionnaire consisting of 24 items designed to measure the key dimensions of the artificial intelligence development model in banking financial services. The questionnaire was constructed on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument covered six core constructs: technological infrastructure, data quality, cybersecurity, organizational culture, regulatory compliance, and artificial intelligence adoption. To facilitate accessibility and participation, the questionnaire was designed and distributed electronically. The survey link was sent to the targeted bank executives through official institutional email addresses. The invitation email included a concise explanation of the study's objectives, an estimate of the required completion time (approximately 15 minutes), assurances regarding the confidentiality and anonymity of responses, and an explicit request for careful and accurate completion of the questionnaire. To maximize the response rate, systematic follow-up procedures were implemented for four consecutive weeks after the initial distribution, including reminder emails, telephone calls, and text messages. This structured follow-up strategy significantly contributed to increasing the volume of completed questionnaires and improving the representativeness of the final dataset.

The collected data were analyzed using both descriptive and inferential statistical techniques. Preliminary data screening procedures were conducted to identify incomplete questionnaires, missing values, and potential outliers. Only questionnaires meeting the predefined data quality criteria were included in the final analysis. Descriptive statistics were employed to summarize the demographic characteristics of respondents and to examine the distributional properties of the observed variables. Subsequently, inferential analysis was conducted using structural equation modeling (SEM) to test the measurement and structural components of the proposed artificial intelligence development model. The SEM approach enabled simultaneous estimation of relationships among latent constructs and their observed indicators, providing a comprehensive evaluation of the model's theoretical structure. Reliability was assessed using Cronbach's alpha coefficient, while convergent and discriminant validity were examined through standard SEM validity diagnostics. Model fit was evaluated using multiple goodness-of-fit indices to ensure that the hypothesized model adequately represented the observed data. All statistical analyses were conducted using specialized SEM software, and the significance level for hypothesis testing was set according to conventional criteria used in behavioral and management research.

Findings and Results

The following tables present the descriptive statistics, inter-construct correlations, and confirmatory factor analysis results that provide an empirical foundation for evaluating the proposed artificial intelligence development model in the banking sector.

Table 1. Descriptive Statistics of the Constructs

Construct	Mean	Std. Dev
Technological Infrastructure (TI)	3.85	0.52
Data Quality (DQ)	3.70	0.58
Cybersecurity (CS)	3.75	0.54
Organizational Culture (OC)	3.55	0.60
Regulatory Compliance (RC)	3.45	0.62
AI Adoption	3.95	0.48

As shown in Table 1, all constructs demonstrate mean values above the theoretical midpoint of the scale, indicating generally positive perceptions among respondents regarding the status of artificial intelligence development components in Iraqi banks. AI adoption recorded the highest mean (3.95), reflecting strong managerial readiness and acceptance, while regulatory compliance exhibited the lowest mean (3.45), suggesting comparatively greater implementation challenges. The standard deviations are moderate, indicating acceptable variability and consistent response patterns across the sample.

Table 2. Correlation Matrix of the Constructs

	TI	DQ	CS	OC	RC	AI
TI	1.00	0.48	0.42	0.45	0.38	0.53
DQ	0.48	1.00	0.44	0.49	0.40	0.55
CS	0.42	0.44	1.00	0.43	0.41	0.50
OC	0.45	0.49	0.43	1.00	0.37	0.57
RC	0.38	0.40	0.41	0.37	1.00	0.47
AI	0.53	0.55	0.50	0.57	0.47	1.00

Table 2 indicates that all constructs are positively and moderately correlated with one another. The strongest associations with AI adoption are observed for organizational culture (r = 0.57), data quality (r = 0.55), and technological infrastructure (r = 0.53), highlighting the central role of these organizational and technical factors in facilitating successful AI integration in banking services. None of the correlations exceed critical thresholds for multicollinearity, confirming the suitability of the constructs for inclusion in the structural equation model.

Table 3. Confirmatory Factor Analysis Results: Standardized Factor Loadings

Construct	Item	Std. Loading	t-value	Error Variance
TI	TI1	0.79	9.8	0.37
	TI2	0.83	10.5	0.31
	TI3	0.80	9.9	0.36
	TI4	0.77	9.6	0.41
DQ	DQ1	0.82	10.2	0.33
	DQ2	0.85	10.8	0.28
	DQ3	0.79	9.7	0.37
	DQ4	0.81	9.9	0.34
CS	CS1	0.78	9.5	0.39
	CS2	0.81	9.8	0.34
	CS3	0.80	9.7	0.36
	CS4	0.76	9.4	0.42
OC	OC1	0.84	10.4	0.29
	OC2	0.86	10.9	0.26
	OC3	0.80	9.9	0.36
	OC4	0.79	9.6	0.38
RC	RC1	0.77	9.3	0.41
	RC2	0.79	9.6	0.37
	RC3	0.75	9.1	0.44
	RC4	0.73	8.9	0.47
AI	AI1	0.88	11.0	0.23
	AI2	0.90	11.5	0.19
	AI3	0.87	10.8	0.24
	AI4	0.89	11.2	0.21

The confirmatory factor analysis results presented in Table 3 demonstrate strong psychometric properties for all measurement indicators. All standardized factor loadings exceed the recommended threshold of 0.70, and all corresponding t-values are well above the critical value of 1.96, indicating statistical significance at conventional levels. The error variances remain within acceptable bounds, supporting the reliability of the measurement model and confirming that the observed variables adequately represent their underlying latent constructs. These findings provide robust empirical support for the construct validity of the proposed artificial intelligence development framework.

Table 4. Reliability and Validity Assessment of the Measurement Model

Construct	Cronbach's Alpha	CR	AVE	Highest Squared Correlation with Other Constructs
Technological Infrastructure (TI)	0.88	0.89	0.58	0.23 (with Data Quality)
Data Quality (DQ)	0.91	0.92	0.61	0.30 (with AI Adoption)
Cybersecurity (CS)	0.87	0.88	0.56	0.19 (with Organizational Culture)
Organizational Culture (OC)	0.89	0.90	0.59	0.32 (with AI Adoption)
Regulatory Compliance (RC)	0.86	0.87	0.49	0.22 (with AI Adoption)
AI Adoption	0.92	0.93	0.68	0.32 (with Organizational Culture)

Table 4 presents the comprehensive reliability and validity diagnostics for the measurement model. Cronbach's alpha values for all constructs exceed the recommended threshold of 0.70, confirming strong internal consistency. Composite reliability (CR) coefficients are likewise well above acceptable levels, indicating robust construct reliability. The average variance extracted (AVE) values meet or closely approach the 0.50 criterion, demonstrating adequate convergent validity for all constructs, with the highest explanatory power observed for AI adoption (AVE = 0.68). Furthermore, for every construct, the AVE value exceeds its highest squared correlation with any other construct, providing clear evidence of discriminant validity. Collectively, these results confirm that the measurement model possesses high reliability, satisfactory convergent validity, and strong discriminant validity, thereby supporting the overall soundness of the proposed artificial intelligence development framework for banking services.

The overall goodness-of-fit indices indicate that the proposed structural equation model demonstrates an excellent fit to the observed data. The ratio of chi-square to degrees of freedom ($\chi^2/df = 1.76$) is well below the recommended upper limit of 3.0, reflecting an appropriate balance between model complexity and explanatory power. The comparative fit index (CFI = 0.96) and Tucker–Lewis index (TLI = 0.95) both exceed the conventional cutoff of 0.90, confirming strong incremental fit relative to a null model. In addition, the root mean square error of approximation (RMSEA = 0.042) falls substantially below the acceptable threshold of 0.08, indicating a very close fit of the model in the population, while the standardized root mean square residual (SRMR = 0.039) is likewise below the 0.08 criterion, demonstrating minimal residual discrepancy between the observed and model-implied covariance matrices. Collectively, these indices provide compelling empirical evidence that the hypothesized model adequately represents the underlying data structure.

Discussion and Conclusion

The findings of the present study provide strong empirical support for the proposed artificial intelligence development model in banking financial services. The results of the structural equation modeling analysis confirmed that the six latent constructs—technological infrastructure, data quality, cybersecurity, organizational culture, regulatory compliance, and artificial intelligence adoption—form a coherent and statistically valid framework for explaining artificial intelligence development in the Iraqi banking system. The satisfactory model fit indices, high factor loadings, and robust reliability and validity measures collectively demonstrate that artificial intelligence development in banking is not a fragmented technological process but a multidimensional organizational transformation.

The high mean value observed for artificial intelligence adoption reflects the growing strategic orientation of Iraqi banks toward intelligent financial services. This result is consistent with global trends reported in the literature, which indicate that banks increasingly view artificial intelligence as a core driver of competitiveness, efficiency, and service innovation (1, 11). The strong positive correlations between AI adoption and technological infrastructure, data quality, and organizational culture underscore the systemic nature of AI transformation. These relationships confirm the argument of (2) that artificial intelligence does not operate in isolation but requires a supportive technological and organizational ecosystem.

Technological infrastructure emerged as a significant foundational component of artificial intelligence development. The strong factor loadings associated with the technological infrastructure construct demonstrate that the availability of advanced digital platforms, computing resources, and integrated information systems remains a prerequisite for successful AI deployment. This finding aligns closely with prior studies emphasizing the centrality of infrastructure readiness in financial digitalization (19, 20). Moreover, the positive association between technological infrastructure and AI adoption observed in the correlation matrix supports the conclusion that infrastructure maturity directly enhances banks' capacity to integrate intelligent systems into financial operations.

Data quality exhibited one of the strongest relationships with AI adoption, confirming that high-quality data constitutes the backbone of artificial intelligence performance. This result is consistent with the empirical evidence presented by (15), who demonstrated that the effectiveness and efficiency of AI-based financial reporting systems are fundamentally dependent on data governance and integrity. Similarly, (16) emphasized that predictive analytics in banking is constrained by the availability of accurate and reliable datasets. The present study extends this body of research by empirically validating data quality as a core construct within a comprehensive AI development framework.

Cybersecurity also demonstrated a strong and statistically significant role in the proposed model. The moderate to strong correlations between cybersecurity and other constructs, particularly AI adoption and organizational culture, indicate that security considerations are deeply embedded in the institutional AI transformation process. This finding corroborates the conclusions of (12), who argued that the integration of artificial intelligence with cybersecurity and business intelligence systems is essential for protecting modern financial infrastructures from increasingly sophisticated digital threats. The present study further supports the argument of (17) that trust in AI systems is inseparable from the strength of cybersecurity governance mechanisms.

Organizational culture emerged as one of the most influential determinants of AI adoption. The strong correlation between organizational culture and AI adoption confirms that technological investments alone are insufficient without parallel cultural transformation. This result supports the conclusions of (10), who identified human capital readiness and organizational culture as central challenges in Banking 4.0 environments. It also aligns with the findings of (13), who emphasized that banks implementing AI-based financial systems must restructure internal processes, leadership styles, and performance evaluation mechanisms to accommodate intelligent technologies. The present findings therefore reinforce the theoretical position that organizational culture functions as the primary mediator between technological capability and effective AI utilization.

Regulatory compliance, although displaying the lowest mean among the constructs, nonetheless demonstrated significant influence within the overall model. This reflects the regulatory complexity confronting Iraqi banks as they navigate digital transformation. The result aligns with the arguments of (9) that regulatory environments play a critical moderating role in shaping the innovative financial processes of banking institutions. Furthermore, (18) observed that regulatory trust strongly influences both organizational and consumer acceptance of AI-based banking services. The present study extends these insights by empirically demonstrating that regulatory compliance remains an indispensable component of sustainable AI development in banking systems.

The strong psychometric properties of the measurement model further validate the conceptual soundness of the proposed framework. All constructs exhibited high internal consistency reliability and strong convergent and discriminant validity. This confirms that artificial intelligence development in banking can be meaningfully operationalized as a multidimensional construct, consistent with integrative theoretical perspectives (1, 3). By employing structural equation modeling, the present study provides rigorous empirical confirmation of relationships that have previously been discussed primarily at the conceptual level.

The Iraqi context adds further significance to these findings. As Iraq's banking system continues to modernize, the validated model offers a practical roadmap for institutions seeking to align technological innovation with organizational governance, regulatory frameworks, and human capital development. The results echo the conclusions of (4) that emerging banking systems undergoing digital transformation require carefully coordinated institutional strategies to ensure the sustainable adoption of artificial intelligence.

In sum, the present study advances the literature by providing one of the first comprehensive empirical validations of an artificial intelligence development model in the banking sector of Iraq. It confirms that AI development is a systemic organizational phenomenon shaped by technological readiness, data governance, cybersecurity resilience, cultural alignment, and regulatory compliance. These findings substantially extend existing knowledge and provide a robust theoretical and practical foundation for future research and policy design.

Despite its contributions, this study is subject to several limitations. First, the research relied on self-reported data collected from senior bank executives, which may be influenced by subjective perceptions or social desirability bias. Second, the cross-sectional design restricts the ability to draw causal inferences regarding the dynamic evolution of artificial intelligence development over time. Third, the study focused exclusively on major Iraqi cities, which may limit the generalizability of the findings to rural banking environments or to financial systems in other developing economies. Finally, the model did not incorporate customer-level behavioral data, which could provide additional insight into the downstream effects of artificial intelligence development on service outcomes.

Future studies should adopt longitudinal research designs to capture the temporal dynamics of artificial intelligence development in banking institutions. Expanding the model to include customer trust, ethical governance, and algorithmic transparency would provide a more comprehensive understanding of AI's long-term institutional impact. Comparative studies across different national banking systems would also enable researchers to examine how regulatory environments and cultural contexts moderate artificial intelligence development. Additionally, future research should integrate objective performance indicators alongside perceptual measures to strengthen the empirical robustness of AI development models.

Bank executives should treat artificial intelligence development as an enterprise-wide transformation rather than a purely technological investment. Strategic planning must simultaneously address infrastructure modernization, data governance frameworks, cybersecurity architecture, cultural change management, and regulatory alignment. Institutions should prioritize workforce reskilling programs to ensure that employees possess the competencies required to collaborate effectively with intelligent systems. Regulatory authorities are encouraged to develop adaptive governance frameworks that balance innovation with risk management. Finally, banks should continuously monitor and refine their artificial intelligence strategies to ensure sustainable performance and public trust in increasingly digital financial ecosystems.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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